

An Enhanced Differential Evolution Based on Center Mutation for Environmental Economic Dispatch

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Abstract: In order to improve the convergence of multi-objective differential evolution (DEMO) algorithm while ensuring well distribution, a new method of center mutation-based DEMO (CM-DEMO) is proposed. Firstly, the form of mutation is improved, the center of the population in the current generation is taken as a base vector, and then the direction of difference vector is determined according to the fitness value of the three random vectors of individuals, secondly, the strategy of adaptive crossover probability is given, the crossover probability is determined according to the distribution of fitness value in the population. Test of benchmark functions show that CM-DEMO algorithm has faster convergence rate. Finally, CM-DEMO is applied to environmental economic dispatch of power system. Compared with other methods, the simulation results obtained demonstrate the feasibility and effectiveness of the proposed algorithm for solving the problem.

Keywords: Differential evolution; Multi-objective optimization; Center mutation; Environmental economic dispatch

1 Introduction

Many real world problems can be formulated as optimization problems with multiple objectives. Since the first attempt to solve multi-objective optimization problems by using evolutionary algorithms, multi-objective evolutionary algorithms(MOEAs) have been much researched and are widely used to solve numerous applications in recent years (Coello, 2006; Nam & Park, 2000). MOEAs benefit from the evolutionary algorithm's ability to generate a set of solutions concurrently in a single run thereby yielding several trade-off solutions.

Differential evolution (DE) is a new generation evolutionary algorithm (EA) and has been successfully applied to solve a wide range of optimization problems. Differential evolution (DE) is a new type of evolutionary algorithm proposed by Storn and Price in 1995 (1997). It is simple yet powerful, and has been successfully used in solving single objective optimization problems. In recent years, some researchers have extended it to deal with multi-objective optimization problems, such as Pareto differential evolution (PDE) algorithm (Abbass, 2002; Xue, Sanderson & Graves, 2003), Pareto-based multi-objective differential evolution (PMODE) (Madavan, 2002) differential evolution for multi-objective optimization (DEMO) and adaptive differential evolution algorithm (ADEA) (Robic & Filipic, 2005; Qian & Li, 2008).

However, most of these DE based multi-objective optimization algorithms suffer from premature convergence

at different degrees (Madavan, 2002; Robic & Filipic, 2005; Qian & Li, 2008). In this paper, we present a new multi-objective optimization of center mutation-based DEMO (CM-DEMO). The CM-DEMO has two improvements: a mutation operator composed of the modified base vector and differential vectors, the former is set as the center of all target vectors, and the latter is determined by the function fitness value of three randomly selected vectors; an adaptive crossover probability process according to the distribution of the function fitness value. For illustration, CM-DEMO was applied to solve the environmental economic dispatch problem, which consists of four interconnected cascade hydro plants and a thermal plant. Simulated results demonstrate the feasibility and effectiveness of the proposed method.

The rest of the paper is organized as follows: The DE principle which CM-DEMO is based on is briefly described in Section 2. Afterward, in Section 3, we present CM-DEMO for solving problem in details. Section 4 presents the application study of CM-DEMO to a practical environmental economic dispatch problem. Section 5 outlines the conclusions followed by acknowledgements.

2 Overview of Differential Evolution

DE algorithm is a population based algorithm using three operators; crossover, mutation and selection. Several optimization parameters must also be tuned (Storn & Pric, 1997). The approach uses a population P^g that contains NP n-dimensional real-valued parameter vectors (named x_i^g) in generation g. According to Storn and Price, DE's strategy can be described as follows.

2.1 Mutation

For each target vector x_i^g , $i=1,2,\dots, NP$ a mutant vector v_i^{g+1} is generated according to (Storn & Pric, 1997):

$$v_i^{g+1} = x_{r_1}^g + (x_{r_2}^g - x_{r_3}^g), \quad i=1,2,\dots, NP \quad (1)$$

where integers r_1 , r_2 and r_3 are chosen randomly in the range $[1, N_p]$, and are different from each other. The mutation parameter F ($[0, 2]$) is a real, constant, user-supplied parameter that controls the amplification of the differential vector (named ∇).

2.2 Crossover

In order to increase the diversity of the perturbed parameter vectors, crossover is introduced. The target vector is mixed with the mutated vector, using the following scheme, to yield the trial vector u_i^{g+1} , as follows (Storn & Pric, 1997):

$$u_{i,j}^{g+1} = \begin{cases} v_{i,j}^{g+1}, & \text{if } (\text{random}() \leq CR) \text{ or } j = \text{randomRange}(1, n) \\ x_{i,j}^g, & \text{otherwise} \end{cases} \quad (2)$$

In the above, function random () generates a random number in $[0, 1]$, CR ($\in [0, 1]$) is the crossover

parameter, and the integer j is a randomly chosen index in $\{1, 2, \dots, n\}$ that ensures candidate u_i^{g+1} get at least one parameter from trial parameter vector v_i^{g+1} but not all from $x_{i,j}^g$.

2.3 Selection

When selection operation is implemented, a knock-out competition is played between the target vector x_i^g and its corresponding trial vector u_i^{g+1} . According to the value of fitness, the better one will be selected for the next generation. Assuming that the fitness value is to be minimized, the selection operation can be expressed as (Storn & Pric, 1997):

$$x_i^{g+1} = \begin{cases} u_i^{g+1}, & \text{if } u_i^{g+1} \text{ better than } x_i^g \\ x_i^g, & \text{otherwise} \end{cases} \quad (3)$$

3 An Enhanced Multi-objective Differential Evolution: CM-DEMO

In this section, by analyzing the mutation and crossover operation in the process of algorithm, the center mutation-based DEMO (CM-DEMO) algorithm is proposed. First, the CM-DEMO algorithm will be described in details, and then several typical and widely used benchmark test problems are chosen to test CM-DEMO.

3.1 Center mutation operator

From (1) we can conclude that DE algorithm randomly selects two individuals to calculate the difference as the difference vector, here the direction of difference vector is ignored. In this condition, the search capability is improved to some extent, but the convergence rate of the algorithm is slow down. In this section an operator called the center mutation operator is proposed, that is, each individual by mutation is around the center of contemporary population. The specific form of mutation operator is described as follows

$$V_i^{g+1} = C^g + F * (X_o^g - X_1^g) + F * (X_o^g - X_2^g) \quad (4)$$

Where, X_o is the best individual in the three random individuals; X_1 and X_2 are the other two random individuals; C is the center of population.

Formula (4) shows that for each mutation individual, it is calculated based on the fitness value of the three random individual, then starts from the group center toward the of best individual X_o . Here the direction which X_o point to is the direction of difference vector, making the improved mutation operator not only retain a certain degree of randomness, but also the guidance of certainty is considered. Thus, under the action the center mutation operator, the new algorithm will have a faster convergence speed.

3.2 Adaptive crossover probability

In the standard DE algorithm, fixed CR is commonly used, that is in the process of solving problems, the crossover probability of each individual is identified with a certain value. However, in solving practical problems, the value should be adjusted appropriately based on the iteration cycle and the function values of each individual, making the algorithm acted in line with the characteristics of problem. Here a method of adaptive crossover probability is presented in Equation 5 (take the minimize problem as the case)

$$CR_i = \begin{cases} \max \left[\left| \frac{F_i - F_o}{F_i - F_{\min}} \right|, \left| \frac{F_i - F_o}{F_{\max} - F_{\min}} \right| \right], & F_i > F_o \\ \min \left[\left| \frac{F_i - F_{\min}}{F_{\max} - F_{\min}} \right|, \left| \frac{F_o - F_i}{F_{\max} - F_{\min}} \right| \right], & other \end{cases} \quad (5)$$

Where CR_i is the crossover probability of each individual; F_i and F_o are the function values of the individuals X_i and X_o ; F_{\min} and F_{\max} are the values of the best and worst individuals in current generation.

Formula (5) shows that, when $F_i > F_o$, the crossover probability should be increased, in order to generate more mutation individuals V_i in the new individuals, the adjustment strategy is: by comparing the proportion which F_i to the current generation and the proportion which F_o to F_i , the greater proportion is choose as the value of crossover probability of the target individual; when $F_i \leq F_o$, the crossover probability should be reduced, then individual X_i take more components in the new individuals, the adjustment strategy is: by comparing the proportion which F_i to the current generation and the proportion which F_o to F_i , the smaller proportion is choose as the value of crossover probability. This method can effectively adjust the composition of the individual generated according to the function value of individuals in iterative process, and then the search performance of algorithm is improved.

3.3 Outline of CM-DEMO

According to the above description of the improved algorithm, the outline of CM-DEMO is described as follows:

Table 1. The main procedure of ε -ODEMO

Algorithm: Main procedure of the proposed CM-DEMO
Initialize population randomly;
While the halting criterion is not satisfied do
Calculate the fitness function;
Mutation according to formula (4);
Calculate CR according to formula (5), crossover according to formula (2);
Choose according to formula (2);
end while

3.4 Performance test

The test problems for evaluating the performance of our methods are chosen based on significant past studies in multi-objective evolutionary algorithms. We chose four problems from benchmark to test CM-DEMO (Zitzler & Thiele, 2000; Deb, Thiele, Laumanns & Zitzler, 2005).

For every test problem: a crossover probability CR was set to 0.5, scaling factor F was set to 0.5. In order to make the comparisons fair, the population size NP was set to 100 and the algorithm was run for 250 generations.

Figures 1-4 show the Pareto fronts obtained by CM-DEMO and the real Pareto fronts of four ZDT test problems. As can be seen, solutions obtained by CM-DEMO scale very well in terms of convergence and widely-distributed.

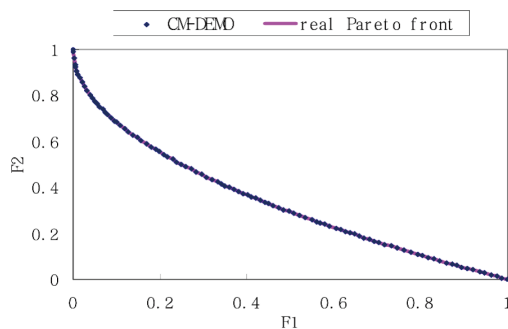


Figure 1. Pareto front for ZDT1

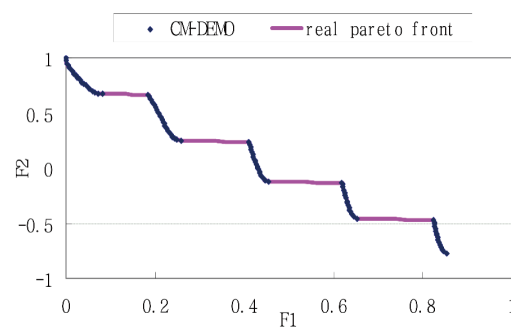


Figure 2. Pareto front for ZDT3

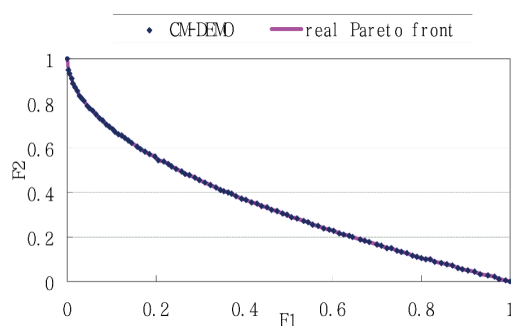


Figure 3. Pareto front for ZDT4

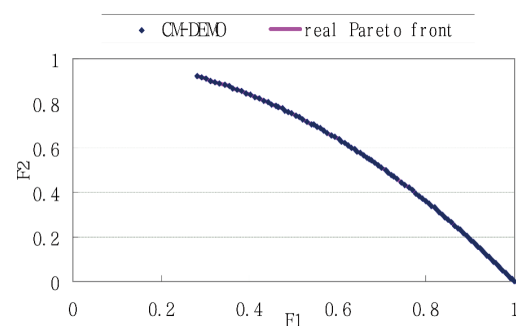


Figure 4. Pareto front for ZDT6

Tables 2 present the mean (boldfaced font above) and variance (underside) of the values of the convergence and diversity metric averaged over 10 runs (Deb & Jain, 2002; Van Veldhuizen, 1999). Results of other algorithms are taken from the literatures (NSGA- II, SPEA2, PDEA, DEMO, ADEA and DEMO/parent).

Table 2. Statistics of results on convergence metric γ and diversity metric Δ

Metrics	Problems	NSGA-II (real-coded)	SPEA2	DEMO	PDEA	ADEA	PDEMO	CM- DEMO
γ	ZDT1	0.033482	0.023285	0.001083	/	0.002741	0.005800	0.000028
		0.004750	0	0.000113	/	0.000385	0	0
	ZDT3	0.114500	0.018409	0.001178	/	0.002741	0.021560	0.00017
		0.007940	0	0.000059	/	0.000120	0	0
	ZDT4	0.513053	4.9271	0.001037	/	0.100100	0.638950	0.002190
		0.118460	2.703	0.000134	/	0.446200	0.500200	0.000097
	ZDT6	0.296564	0.232551	0.000629	/	0.000624	0.026230	0.000016
		0.013135	0.004945	0.000044	/	0.000060	0.000861	0
Δ	ZDT1	0.390307	0.154723	0.325237	0.298576	0.382890	/	0.146883
		0.001876	0.000874	0.030249	0.000742	0.001435	/	0.000062
	ZDT3	0.738540	0.469100	0.309436	0.623812	0.525770	/	0.433462
		0.019706	0.005265	0.018603	0.000225	0.043030	/	0.000453
	ZDT4	0.702612	0.823900	0.359905	0.840852	0.436300	/	0.157800
		0.064648	0.002883	0.037672	0.035741	0.110000	/	0.000305
	ZDT6	0.668025	1.04422	0.442308	0.473074	0.361100	/	0.114263
		0.009923	0.158106	0.021721	0.021721	0.036100	/	0.001769

The results of convergence metric(see Table 2) for these three problems show that CM-DEMO achieves good convergence, which is rather better than PDEA, DEMO, and DEMO/parent, and much better than NSGA- II and SPEA2. On ZDT3, DEMO achieves comparable results to CM-DEMO, but on ZDT1 and ZDT6, CM-DEMO performances better. For another metric Δ , showed in Table 2 CM-DEMO achieves much better results on four test problems than the other algorithms referred here.

ZDT4 is a difficult optimization problem with large number of local Pareto fronts that tend to mislead the optimization algorithm. In Table 2 we can see that NSGA- II, SPEA2, PDEA and MODE all have difficulties in converging to the true Pareto front. DEMO, CM-DEMO performs better than the other algorithms.

Problem Tamaki is constrained test problem and DTLZ1 is high-dimension problem (M=3). Figures 5 and 6 show the Pareto fronts obtained by CM-DEMO.

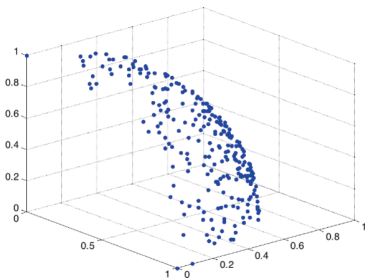


Figure 5. Pareto front for Tamaki

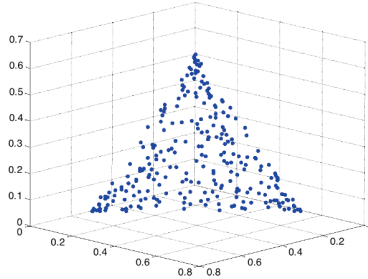


Figure 6. Pareto front for DTLZ1

From Figures 5 and 6 we can see that CM-DEMO handled constraints and high-dimension problem well, also it converged to the true Pareto front accurately. After achieving good performance on test problems, next we will apply CM-DEMO to a practical problem of environmental economic dispatch of power systems.

4 Case Sstudy

In order to validate the proposed procedure, a test hydrothermal system is taken for case study (Naresh & Sharma, 1999). The system consists of a multi-chain cascade of four hydro plants and three thermal units. The details data of the system considered here are the same as in Ref.

4.1 Hydrothermal scheduling problem

The solution of environmental economic dispatch problem aims to minimize the operation costs of thermal power plant and contaminative gas emission simultaneously, while satisfying a series of equality and inequality constraints (Talaq, El-Hawary & El-Hawary, 1994; Yalcinoz & Köksoy, 2007; Abido, 2003).

4.1.1 Problem objectives

(1) Economy objective

The generator cost curves are represented by quadratic functions of real power generation by that unit, the total fuel cost can be formulated as:

$$\min f_1 = \sum_{t=1}^T \sum_{i=1}^{N_s} [f'_i(P'_{si})] = \sum_{t=1}^T \sum_{i=1}^{N_s} [a_{si} + b_{si} \cdot P'_{si} + c_{si} \cdot (P'_{si})^2 + |d_{si} \sin(e_{si}(P_{si}^{\min} - P'_{si}))|] \quad (6)$$

where a_{si} , b_{si} and c_{si} are the cost curve coefficients of the i th thermal unit, $P_{si}(t)$ is the output power of the i th thermal unit at period t , d_{si} , e_{si} are the valve-point effects coefficients of the i th thermal plant; P_{si}^{\min} is the minimum output limit of the i th thermal plant.

(2) Emission objective

Since SO₂ and NO_x emissions are generally taken to be proportional to the generator's fuel consumption, total emission function to represent SO₂ and NO_x emissions are used in this paper is the same form as that of the fuel cost function. Hence, the total emission of the hydro-thermal system can be expressed as:

$$\min f_2 = \min \sum_{t=1}^T \sum_{i=1}^{N_s} [a_{si} + \beta_{si} P_{si}(t) + \gamma_{si} P_{si}^2(t) + \eta_{si} \exp(\delta_{si} P_{si}(t))] \quad (7)$$

where a_{si} , β_{si} , γ_{si} , η_{si} , and δ_{si} are emission curve coefficients of the i th thermal unit.

4.1.2 System constraints

The problem subjects to is subjected to the following equality and inequality constraints:

(3) Power balance constraints

$$\sum_{i=1}^{N_s} P_{i,t}^s + \sum_{j=1}^{N_h} P_{j,t}^h - P_{D,t} - P_{L,t} = 0, \quad t = 1, 2, \dots, T \quad (8)$$

where $P_{D,t}$ is the load demand at period t , $P_{L,t}$ the total transmission line losses at period t , $P_{i,t}^h$ is the output power of the j th hydro plant at period t , and N_h is the number of hydroelectric plants.

(4) Real power output limits

$$P_{i,\min}^s \leq P_{i,t}^s \leq P_{i,\max}^s, \quad i = 1, \dots, N_s \text{ and } P_{j,\min}^h \leq P_{j,t}^h \leq P_{j,\max}^h, \quad i = 1, \dots, N_h \quad (4)$$

where, $P_{j,\min}^h$ and $P_{j,\max}^h$ are the lower and upper generation limits of the j th hydroelectric plant, respectively.

(5) Reservoir storage volumes limits

$$V_{j,\min} \leq V_{j,t} \leq V_{j,\max}, \quad j = 1, \dots, N_h \quad (9)$$

where $V_{j,\min}$ and $V_{j,\max}$ are the minimum and maximum storage volume of the j th reservoir, respectively.

(6) Hydro plant power limits

$$Q_{j,\min} \leq Q_{j,t} \leq Q_{j,\max}, \quad j = 1, \dots, N_h \quad (10)$$

where $Q_{j,\min}$ and $Q_{j,\max}$ are the minimum and maximum water discharge rate of the j th hydroelectric plant, respectively.

(7) Initial and terminal reservoir storage volumes

$$V_{j,0} = V_j^{begin}, \quad V_{j,T} = V_j^{end}, \quad j = 1, \dots, N_h \quad (11)$$

where V_j^{begin} and V_j^{end} are the initial and final storage volume of reservoir j .

(8) Water dynamic balance equation with travel time

$$V_{j,t+1} = V_{j,t} + \left[I_{j,t} - Q_{j,t} - S_{j,t} + \sum_{k=1}^{N_{uj}} (Q_{k,t-T_{kj}} + S_{k,t-T_{kj}}) \right] \cdot \Delta t \quad (12)$$

where $I_{j,t}$ is the nature inflow rate of the j th reservoir at period t , N_{uj} is the number of upstream units directly above the j th hydroelectric plant, $S_{j,t}$ is the spillage of the j th reservoir at time t , and T_{kj} is the water transport delay from reservoir k to j .

(9) Hydroelectric generation relation

$$P_{j,t}^h = C_{1j} \cdot (V_{j,t})^2 + C_{2j} \cdot (Q_{j,t})^2 + C_{3j} \cdot V_{j,t} \cdot Q_{j,t} + C_{4j} \cdot V_{j,t} + C_{5j} \cdot Q_{j,t} + C_{6j} \quad (13)$$

$$j = 1, 2, \dots, N_h, \quad t = 1, 2, \dots, T$$

where C_{1j} , C_{2j} , C_{3j} , C_{4j} , C_{5j} , and C_{6j} are the power generation coefficients of j th hydroelectric plant, $Q_{j,t}$ is the water discharge rate of j th reservoir at period t , $V_{j,t}$ is the storage volume of j th reservoir at period t .

4.2 Solution methodology based on CM-DEMO

In this section, some method of proposed CM-DEMO for solving generation scheduling of this hydrothermal system is described in details. Especially, a suggestion will be given on how to handle constraints of the problem.

4.2.1 Initialization

In the initialization procedure, the population is initialized by creating NP solutions randomly. For all solutions in the initial population, each element is randomly generated within the feasible real power output range to the constraint. For the present problem, it is discharge rate of each hydro plant and the power generated by each thermal unit. Thus the population is initialized as follows:

$$Q_{1,1}, Q_{1,2}, \dots, Q_{1,T}, \dots, Q_{N_h,1}, Q_{N_h,2}, \dots, Q_{N_h,T},$$

$$P_{1,1}^s, P_{1,2}^s, \dots, P_{1,T}^s, \dots, P_{N_s,1}^s, P_{N_s,2}^s, \dots, P_{N_s,T}^s.$$

The dimension $n = [(N_h + N_s) * T]$. $P_{1,2}^s$ is randomly generated between $Q_{j,\min}$ and $Q_{j,\max}$, and $P_{i,t}^s$ is randomly generated between $P_{j,\min}^h$ and $P_{j,\max}^h$. Generally, the newly generated individuals do not satisfy all the constraints and need to be modified by the constraints handling method, described next.

4.2.2 Mutation, crossover and selection

New values of water discharge rate and power generation are generated through mutation and crossover operation according to (8) and (2) respectively. Now, selection is performed by calculate the fitness values of the different individuals. The individuals in the current population are evaluated in the objective space and then assigned a scalar value known as fitness. Depending on the fitness values, individuals will be selected to form the new population. Individuals which have a low fitness value have the chance to be selected. It is worth mentioning that the constraint-handling approach implemented in this study is that the unfeasible

solutions are penalized by assigning a very high value for their fitness.

4.2.3 Constraint handling

Firstly, When population initialization, crossover has been implemented, the new generated solution may not satisfy equality constraints (1) and (5). At present, penalty method is the most popular constraints handling strategy for dealing with this equality constraint at present by using penalty function to punish the infeasible solution during the selection procedure to ensure the priority of feasible ones. However, this strategy may degrade the efficiency of the algorithm remarkably for it requires multiple runs to tune the penalty factors.

Secondly, we focus on handling the output capacity limits (2) and water release limits (4) when the proposed CM-DEMO method is applied to solve environmental economic dispatch problem.

Despite the popularity of penalty functions, they have several drawbacks among which the main one is that they require a careful fine tuning of the penalty factors that accurately estimates the degree of penalization to be applied as to approach efficiently the feasible region. In order to keep the advantages of the penalty function approach and overcome drawback of choice penalty factors, this paper apply an effective constraint handling method for DE, which does not require to set any additional parameters in comparison with the original DE. Therefore, in order to strike a balance between computational efficiency and constraints handling, the following selection strategy is adopted by the proposed CM-DEMO method to choose the better solution while considering the constraints violation during the selection operation:

- (1) If solution P1 is feasible and solution P2 is infeasible, then P1 is favored.
- (2) If both P1 and P2 are feasible, the Pareto-dominance based selection will be implemented to decide which one is better, the selection operation is modified as follows:
 - 1) If the candidate dominates the parent, replace the parent by the candidate.
 - 2) If the parent dominates the candidate, the candidate is discarded.
 - 3) If the candidate and parent are non-dominated with each other, a new population of the size between NP and 2NP is created, and then add the non-dominated candidates and parents into it.
- (3) If both P1 and P2 are infeasible, then the one with smaller constraints violation is favored.

4.3 Simulation results

With the parameter settings listed in Table 3, the proposed method coded by Microsoft Visual C++6.0 language on a Pentium-4 2.0GHz-based processor computer is applied to solve the optimal generation scheduling of this hydrothermal system. The hourly each hydro plant power generation are showed in Table 4. The hourly each reservoir release and storage trajectories are showed in Figures 7 and 8 respectively.

Table 3. Parameter settings for CM-DEMO

Method	Generation number	Population size	Crossover parameter	Scaling factor
CM-DEMO	1000	50	0.5	0.1

Table 4. Hourly hydrothermal power generation scheduling (Unit: 104KW)

Hour	1	2	3	4	5	6	7	8	9	10	11	12
P_{h1}	73.77	79.17	80.44	75.14	78.26	68.15	72.03	79.44	79.42	88.44	84.86	84.38
P_{h2}	52.93	50.04	50.96	53.97	54.09	56.03	61.14	60.82	76.02	67.39	56.32	85.79
P_{h3}	34.60	24.82	27.47	34.86	32.53	22.29	38.23	33.18	37.06	26.93	37.47	28.91
P_{h4}	131.8	129.0	125.7	122.7	115.7	130.8	190.4	223.2	283.0	300.5	289.4	299.1
P_{s1}	104.9	162.6	174.9	104.4	107.9	174.9	174.7	103.9	174.9	175	174.8	174.8
P_{s2}	198.7	193.0	125.2	207.4	196.7	209.2	220.4	211.1	206.9	209.8	234.7	223.7
P_{s3}	153.0	141.3	115.1	51.41	84.73	138.4	192.9	298.2	232.5	211.7	222.2	253.1
Hour	13	14	15	16	17	18	19	20	21	22	23	24
P_{h1}	90.27	78.73	83.22	86.94	84.29	81.08	71.78	65.18	57.31	66.57	59.97	59.23
P_{h2}	82.86	61.42	70.39	72.20	72.34	75.35	63.85	69.08	82.69	88.51	73.67	61.52
P_{h3}	33.14	40.57	42.01	46.76	49.24	51.27	51.76	54.12	54.81	57.39	56.71	57.91
P_{h4}	288.6	304.0	282.5	302.2	295.0	293.2	295.4	276.4	295.3	259.3	288.8	279.5
P_{s1}	174.4	174.9	174.2	174.9	174.9	175	162.2	111.1	137.9	123.2	125.72	120.75
P_{s2}	230.5	215.2	210.5	228.9	210.8	217.2	199.5	179.3	126.7	125.9	195.0	171.0
P_{s3}	210.0	155.0	147.0	147.9	163.2	226.8	225.2	294.6	155.1	139.0	50	50

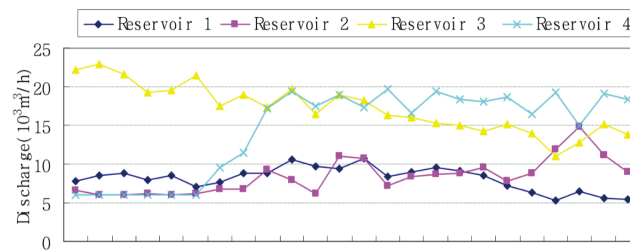


Figure 7. Hourly hydro plant discharge

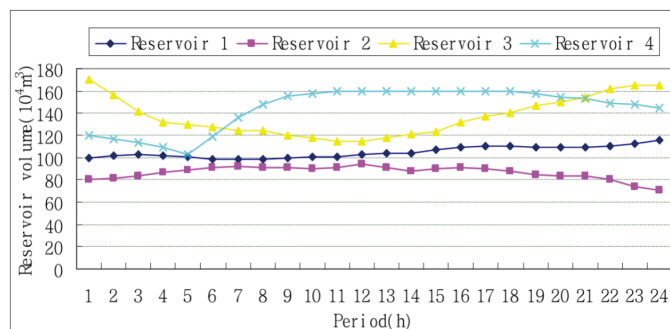


Figure 8. Hourly hydro plant storage

In the meantime, to validate the results obtained with the proposed CM-DEMO method, the same problem is

solved using DEMO, NSGA II, SPEA II methods, the results of test system are also summarized in Table 5 for the convenience of comparisons.

Table 5. Comparisons of schedule results with other methods

Method	Total fuel cost (\$)	Total emission (lb)
CM-DEMO	44781	16870
DEMO	45050	17083
NSGA II	45534	16974
SPEA II	45431	16838

It is clear from Table 3 that the total fuel cost and total emission obtained by CM-DEMO are much less compared to the corresponding values of the other methods. In addition, during these 20 independent simulations, it demonstrates that total fuel cost and total emission generate a variation in a small range with trial numbers when using the proposed CM-DEMO method. As can be seen from the simulation results of CM-DEMO method, the solutions are optimal and they also satisfy various constraints completely for solving environmental economic dispatch problem.

5 Conclusions

In this paper, a modified multi-objective differential evolution optimization algorithm based on center mutation mechanisms has been proposed. The algorithm replaces the original mutation and crossover operation to the improved form, which is center mutation and adaptive crossover. Simulation results and the comparison confirm the effectiveness and the superiority of the proposed approach over the other techniques in terms of the quality and precision of solution, so it provides an effective method to solve the environmental economic dispatch.

References

- Coello, C.A.C. (2006). Evolutionary multi-objective optimization: A historical view of the field. *IEEE Computational Intelligence Magazine*, 1 (1), 28-36.
- Nam, D., & Park, C.H. (2000). Multi-objective simulated annealing: A comparative study to evolutionary algorithms. *International Journal of Fuzzy Systems*, 2 (2), 87-97.
- Storn, R., & Price, K. (1997). Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11, 341-359.
- Abbass, H.A. (2002). *The self-adaptive Pareto differential evolution algorithm*. In: Proc of the Congress on Evolutionary Computation (CEC'2003). Piscataway: IEEE Service Center, 831-836.
- Xue, F., Sanderson, A.C., & Graves, R.J. (2003). *Pareto- based multi-objective differential evolution*. In: Proc of the 2003 Congress on Evolutionary Computation (CEC'2003), Piscataway, NJ: IEEE Press, 862-869.
- Madavan, N.K. (2002). *Multi-objective optimization using a pareto differential evolution approach*. In: Proc of the Congress on Evolutionary Computation (CEC'20002), Piscataway: IEEE Service Center,

(2002) 1145-1150.

Robic, T., & Filipic, B. (2005). *DEMO: Differential Evolution for Multi-objective Optimization*. proceedings of the Third International Conference on Evolutionary Multi-Criterion Optimization(EMO-05), 520-533.

Qian, W., & Li, A.J. (2008). Adaptive differential evolution algorithm for multi-objective optimization problems. *Appl Math Comput*, 201(1-2), 43-40.

Zitzler, E., & Thiele, D.L. (2000). Comparison of multi-objective evolutionary algorithms: Empirical results. *Evolutionary Computation*, 8, 173-195

Deb, K., Thiele, L., Laumanns, M., & Zitzler, E. (2005). Scalable test problems for evolutionary multiobjective optimization. In *Evolutionary multiobjective optimization* (pp. 105-145). Springer, London.

Deb, K., & Jain, S. (2002). Running performance metrics for evolutionary multi-objective optimization.

Van Veldhuizen, D.A. (1999). Multi-objective evolutionary algorithms: classifications, analyzes, and new innovation. Ph.D Dissertation, Department of Electrical and Computer Engineering, Air Force Institute of Technology, Wright-Patterson AFB, OH, May 1999.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6, 182-197.

Zitzler, E., Laumanns, M., & Thiele, L. (2003). SPEA2: improving the strength Pareto evolutionary algorithm. Technical report 103, Computer Engineering and Networks Laboratory (TIK), Swiss Federal Institute of Technology (ETH) Zurich, Gloriastrasse (2003) 35, CH-8092 Zurich, Switzerland.

Naresh, R., & Sharma, J. (1999). Two-phase neural network based solution technique for short term hydrothermal scheduling. *IEE Proc Gener Transm Distrib*, 146(6), 657-63.

Talaq, J.H., El-Hawary, F., & El-Hawary, M.E. (1994). A summary of environmental/economic dispatch algorithms. *IEEE Trans Power Syst*, 9(3), 1508-16.

Yalcinoz, T., & Köksoy, O. (2007). A multiobjective optimization method to environmental economic dispatch. *International Journal of Electrical Power & Energy Systems*, 29(1), 42-50.

Abido, M.A. (2003). A novel multi-objective evolutionary algorithm for environmental/economic power dispatch. *Electric Power Syst Res*, 65(1), 71-81.